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Automated Water Level Control System Using IoT Under Diverse Conditions

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ABSTRACT

Dynamic surface instability often compromises the accuracy of water level management systems. This research presents the design and implementation of a robust Internet of Things (IoT) based system specifically engineered to overcome these environmental challenges. The system utilizes an HY-SRF05 ultrasonic sensor integrated with an automated valve control mechanism to maintain water levels within predefined thresholds. While a Sharp GP2Y0A21YK0F infrared sensor was initially evaluated, it was excluded due to limitations in short-range precision. The unique contribution of this study lies in the rigorous testing of the system under four distinct surface conditions: calm, wavy, foamy, and foamy-wavy, at target heights of 4 cm, 8 cm, and 12 cm. Experimental results demonstrate that the system maintains high accuracy and responsiveness regardless of surface disturbances, effectively filtering out noise caused by foam and waves. Complemented by a web and mobile application for real-time monitoring, this study validates the reliability of the ultrasonic-based solution for automation in volatile fluid environments.

Keywords: *Internet Of Things, Water Level Control, Ultrasonic Sensor, HY-SRF05, Sensor Performance, Automated System*

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INTRODUCTION

Water is a fundamental resource, and its effective management is a critical task across various sectors, including residential, agricultural, and industrial applications (Nurlaili dkk., 2021). Manual monitoring of water levels in tanks or pools is often inefficient, labor-intensive, and prone to human error, leading to water wastage or damaging shortages. The advent of the Internet of Things (IoT) has provided transformative solutions, enabling the development of low-cost, real-time, and automated systems for monitoring and control (Soambaton dkk., 2024). An automated water level control system typically consists of three main parts: a sensing unit to measure the water level, a control unit to process the data, and an actuation unit (like pumps or valves) to adjust the level (Damayanti dkk., 2016). The reliability of the entire system hinges on the accuracy and robustness of the sensing unit. Non-contact sensors, such as ultrasonic and infrared sensors, are often preferred over contact-based sensors (like float switches) because they are less prone to corrosion, fouling, and interference from debris (Daniesar dkk., t.t.).

However, the performance of non-contact sensors can be significantly affected by the physical conditions of the water's surface. In many real-world applications, such as aeration tanks, aquaculture ponds, or even outdoor swimming pools, the water is not perfectly calm. The surface can be wavy, agitated, or covered in foam. These conditions pose a significant challenge. Waves can cause fluctuating readings as the sensor detects the peaks and troughs, while foam can absorb or scatter the sensor's signal, leading to inaccurate measurements or signal loss (Soambaton dkk., 2024). While many studies have demonstrated IoT-based water level monitoring (Prasetya dkk., 2022), a critical gap remains in the literature: the lack of systematic evaluation regarding sensor reliability specifically under the complex combination of wavy and foamy conditions. Most research assumes a calm water surface, which does not reflect the complexity of many real-world environments. Furthermore, few studies validate the performance of a complete, closed-loop control system that must actively regulate water inflow and outflow based on these potentially "noisy" sensor readings.

Directly addressing these limitations, this research designs, implements, and rigorously tests an IoT-based automated water level control system. The primary objective is not merely to build a monitoring tool, but to empirically quantify the performance of a cost-effective ultrasonic sensor (HY-SRF05) under four distinct and challenging water surface conditions: (1) calm, (2) wavy, (3) foamy, and (4) foamy-wavy. By mapping the sensor's behavior in these scenarios, this study aims to determine the viable operational limits for low-cost automation in volatile environments. This study also includes an initial sensor validation phase, comparing the chosen ultrasonic sensor with an infrared sensor (Sharp GP2Y0A21YK0F) to justify its selection for short-range measurements.

The contributions of this paper are twofold: first, it provides a complete blueprint for a low-cost, closed-loop IoT control system, including web and mobile monitoring applications. Second, it presents empirical data on the performance and reliability of the HY-SRF05 sensor in dynamic surface environments, offering valuable insights for engineers and researchers developing similar systems. This study aims to answer the question: Can a low-cost ultrasonic sensor provide reliable data to accurately automate water levels, even when the surface is disturbed by waves and foam?. The remainder of this paper is structured as follows: Section 2 details the research methodology, including the system architecture, the experimental setup, and the data analysis procedures. Section 3 presents the results from both the sensor validation phase and the main experimental tests. Section 4 discusses the interpretation of these results, compares them to existing literature, outlines the study's limitations, and suggests implications for future work. Finally, Section 5 provides the conclusion.

METHOD

This research was conducted following a structured process, which is visualized in Figure 1. The methodology began with a comparative validation of ultrasonic and infrared sensors, which informed the selection of the HY-SRF05 sensor. Following sensor selection, experimental testing was conducted by collecting data under four distinct water conditions (calm, foamy, wavy, and mixed). The collected data was then processed and analyzed to draw final conclusions and recommendations (Widayaka et al., 2022). This section provides a detailed breakdown of the system design, experimental procedures, and analysis methods used.

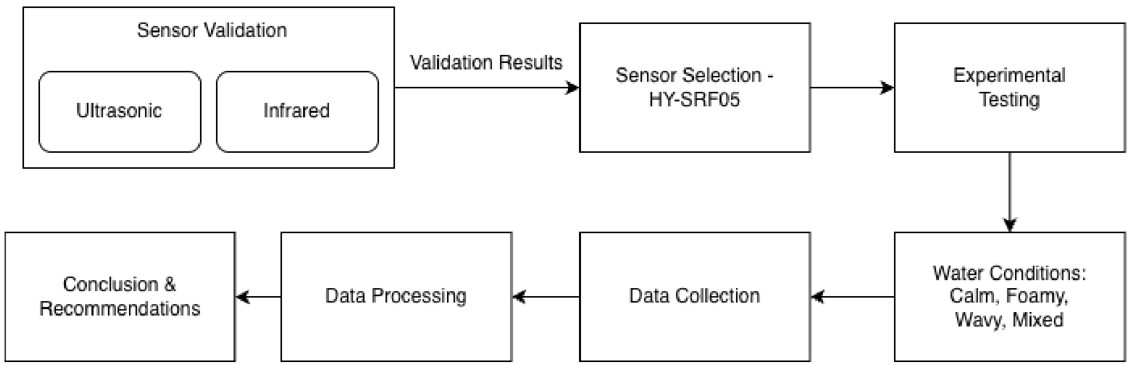

Figure 1. Research Methodology

System Architecture

The IoT system consists of a hardware layer, a software backend, and a front-end monitoring layer.

1. Hardware: The core control unit is an ESP8266 microcontroller, which provides Wi-Fi connectivity. The sensing units evaluated were the HY-SRF05 (Ultrasonic) and the Sharp GP2Y0A21YK0F (Infrared). The actuation unit consists of two Solenoid Valves (for water inflow and outflow), which are controlled by a 2-Channel Relay Module. An LM2596 step-down voltage module was used to provide stable power to the breadboard components. The system was tested using a 20-liter transparent tank as the water reservoir.
2. Software: The system's software architecture is designed for real-time, event-driven communication. The ESP8266 (programmed via Arduino IDE) publishes sensor data and subscribes to control commands using the MQTT protocol, communicating with a HiveMQ broker. A backend API server, developed using Next.js, subscribes to the relevant MQTT topics from HiveMQ, processes the incoming data, and persists it to a MongoDB Atlas database. This Next.js server also provides a REST API for the client applications. For user monitoring, a cross-platform mobile application was developed using Flutter, and a web application was built as part of the Next.js project. These applications fetch data from the API and allow for real-time data visualization and remote manual control of the solenoid valves.

The complete data flow and component interaction for this architecture is visualized in Figure 2. The ESP8266 microcontroller acts as the edge device, gathering data from the sensors and controlling the solenoid valves. It publishes this sensor data to a central HiveMQ (MQTT Broker). The Next.js Backend Server subscribes to this MQTT topic, processes the incoming data, and persists it to the MongoDB Atlas database for historical logging. This server also exposes an API for the client applications, Flutter (Mobile) and Next.js (Web), to retrieve data for user display. For control commands, the applications send a request to the backend, which then publishes a command back to the HiveMQ broker. The ESP8266, being subscribed to this command topic, receives the instruction and actuates the appropriate solenoid valve, thus completing the real-time control loop.

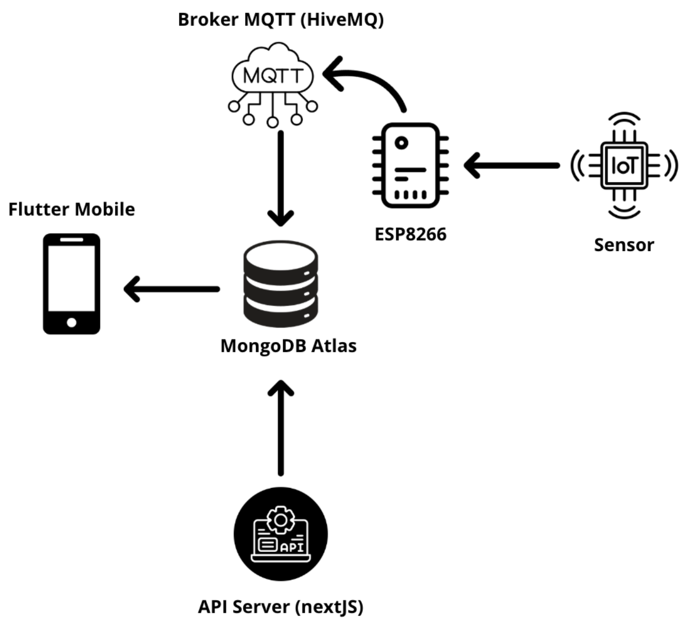

Figure 2. System Architecture Diagram

Sensor Validation and Selection

Before building the full system, an initial validation test was conducted to select the most appropriate non-contact sensor for the target application. The HY-SRF05 (ultrasonic) and GP2Y0A21YK0F (infrared) sensors were tested. The primary requirement was accurate measurement at short distances, specifically targeting levels of 4 cm, 8 cm, and 12 cm from the tank bottom. Both sensors were mounted at a fixed height and aimed at a calm water surface, and the measured distance was recorded.

Experimental Setup and Data Collection Procedure

After selecting the HY-SRF05, the main experiment was conducted.

1. Testbed: The ultrasonic sensor was mounted at a fixed height 20 cm above the tank's maximum water line. A physical ruler was attached to the tank for manual verification of the true water level.
2. Test Conditions: Four distinct water surface conditions were created and tested:
   a. Calm: Still water, no disturbance.

b. Wavy: A small submersible pump or agitator was used to create continuous, non-breaking waves on the surface.
c. Foamy: A surfactant dish soap was added to the water and agitated to create a dense layer of foam.
d. Foamy & Wavy: The wave generator and foam were combined.

3. Data Collection: For each of the four conditions, data was collected at three target water levels: 4 cm, 8 cm, and 12 cm. The system was allowed to stabilize, and sensor readings (distance) were recorded every second for a duration of 5 minutes for each test case. This data, along with timestamps, was sent to the cloud database.

Control System Logic

The automated control logic was programmed into the microcontroller. Two thresholds were defined: a minimum level MIN_LEVEL = 7 cm and a maximum level MAX_LEVEL = 11 cm. The system operates as follows:

1. The sensor continuously measures the water level.
2. IF water_level < MIN_LEVEL: The control unit activates the top tap (inflow valve) and ensures the bottom tap (outflow valve) is closed.
3. IF water_level > MAX_LEVEL: The control unit activates the bottom tap (outflow valve) and ensures the top tap (inflow valve) is closed.
4. IF MIN_LEVEL <= water_level <= MAX_LEVEL: The control unit deactivates both taps, maintaining the water level.

Data Analysis

The raw distance data collected from the sensor was converted to water level height using the formula: Water Level (cm) = Sensor Mounting Height (cm) - Measured Distance (cm) (Based on the data processing, a SENSOR_MOUNT_HEIGHT_CM of 100.0 cm was used). For each of the test cases, statistical analysis was performed using a Python script with the Pandas library. The key metrics calculated were:

1. Mean: The average measured water level ($\overline{x}$), to assess accuracy, as shown in Equation (1).

$$\overline{(x\}} = 1/n \sum (i = 1)^n (x_i) \quad (1)$$

where x_i is the i-th water level measurement and n is the total number of measurements in the test.

2. Standard Deviation (StDev): To measure the precision and stability of the readings (s), as shown in Equation (2). We use the sample standard deviation formula:

$$s = \sqrt{\left(1/(n-1) \sum (i = 1)^n \left(x_i - \overline{(x)}\right)^2\right)} \quad (2)$$

where $\overline{x}$ is the calculated mean of the measurements.

3. Mean Absolute Error (MAE): To quantify the average error between the measured level and the true (target) level, calculated using Equation (3).

$$\mathrm{MAE} = 1/\mathrm{n}\sum(\mathrm{i}=1)^{\mathrm{n}}|\mathrm{x_i} - \mathrm{x_t arget}| \quad (3)$$

where x_{target} is the known target water level 4, 8, or 12 cm.

FINDING AND DISCUSSION

RESEARCH RESULT

Sensor Validation (Ultrasonic vs. Infrared)

The initial sensor validation phase produced a definitive result, as outlined in the research flowchart (Figure 1). Both sensors were tested at the target levels of 4, 8, and 12 cm. The quantitative results for the infrared sensor are presented in Table 1. The data clearly shows that the infrared sensor (GP2Y0A21YK0F) is fundamentally unsuitable for this application. At a target height of 4 cm, the sensor reported a mean water level of 21-25 cm, resulting in a Mean Absolute Error (MAE) of over 17 cm. Similarly, at 8 cm and 12 cm targets, the MAE remained exceptionally high, at 12-15 cm and 4-7 cm, respectively. These results are consistent with the sensor's datasheet, which specifies a much longer minimum detection range. In contrast, preliminary tests with the HY-SRF05 ultrasonic sensor showed accurate readings at these short distances. Consequently, the infrared sensor was rejected, and the HY-SRF05 was selected for all further experiments (Musawi et al., 2020).

Table 1. Performance Results of Infrared Sensor (GP2Y0A21YK0F)

Target Height (cm)	Condition	Mean Level (cm)	Std Deviation (cm)	Mean Absolute Error (MAE)
4	foamy	25.73	0.46	21.73
4	foamy-wavy	24.56	0.91	20.56
4	wavy	23.93	0.92	19.93
4	calm	21.29	0.73	17.29
8	foamy	23.00	0.91	15.00
8	foamy-wavy	22.80	1.18	14.80
8	wavy	21.67	0.84	13.67
8	calm	20.25	0.93	12.25
12	foamy	19.33	0.92	7.33
12	foamy-wavy	18.06	1.14	6.06
12	wavy	17.50	1.05	5.50
12	calm	16.59	0.88	4.59

Ultrasonic Sensor Performance under Diverse Conditions

Following its successful validation, the HY-SRF05 ultrasonic sensor was tested across all 12 experimental cases (3 target heights x 4 conditions). The statistical summary of these tests is presented in Table 2. The results show that the ultrasonic sensor performed with high accuracy and reliability across most conditions. At the 8 cm and 12 cm levels, the Mean Absolute Error (MAE) was consistently low, remaining below 0.8 cm and 0.4 cm, respectively, even in wavy and foamy conditions. This indicates a high degree of accuracy. The Standard Deviation (StDev) serves as a key indicator of reading stability. As expected, the (calm) condition produced the lowest StDev at all levels. The (wavy) and (foamy) conditions introduced more variance, moderately increasing the StDev.

A significant finding was observed in the 4cm target foamy-wavy condition, which showed a dramatically high MAE (7.5 cm) and StDev (6.6 cm). This outlier suggests that at very low water levels, the combination of foam and waves can cause the ultrasonic signal to "lose" the true surface, leading to erratic readings. However, at the more practical operating levels of 8 cm and 12 cm, the sensor remained highly effective.

Table 2. Performance Statistics of Ultrasonic Sensor (HY-SRF05)

Target Height (cm)	Condition	Mean Level (cm)	Std Deviation (cm)	Mean Absolute Error (MAE)
4	foamy	4.67	0.39	0.67
4	foamy-wavy	11.50	6.60	7.50
4	wavy	5.17	1.25	1.17
4	calm	4.96	0.39	0.96
8	foamy	7.59	0.37	0.48
8	foamy-wavy	8.35	0.82	0.62
8	wavy	8.81	0.77	0.81
8	calm	8.68	0.63	0.68
12	foamy	11.64	0.35	0.36
12	foamy-wavy	12.01	0.63	0.31
12	wavy	11.90	0.50	0.17
12	calm	11.91	0.25	0.09

To better visualize the stability data presented in Table 2, Figure 3 plots the standard deviation for each experimental run. The chart clearly illustrates the impact of surface agitation on sensor reading variance. The 'Calm' condition provides a baseline, showing minimal standard deviation (high stability) across all target heights. The 'Foamy' condition introduces only a minor increase in variance. As expected, the 'Wavy' condition significantly increases the standard deviation, as the sensor accurately captures the surface's movement. The most critical finding is visualized in the 'Foamy & Wavy' condition: while the 8cm and 12cm targets show high but consistent variance, the 4cm target (blue bar) shows a dramatic outlier with a standard deviation exceeding 6 cm. This visual evidence reinforces the finding in Table 2, suggesting a potential boundary limit for the sensor's reliability in shallow, highly turbulent conditions.

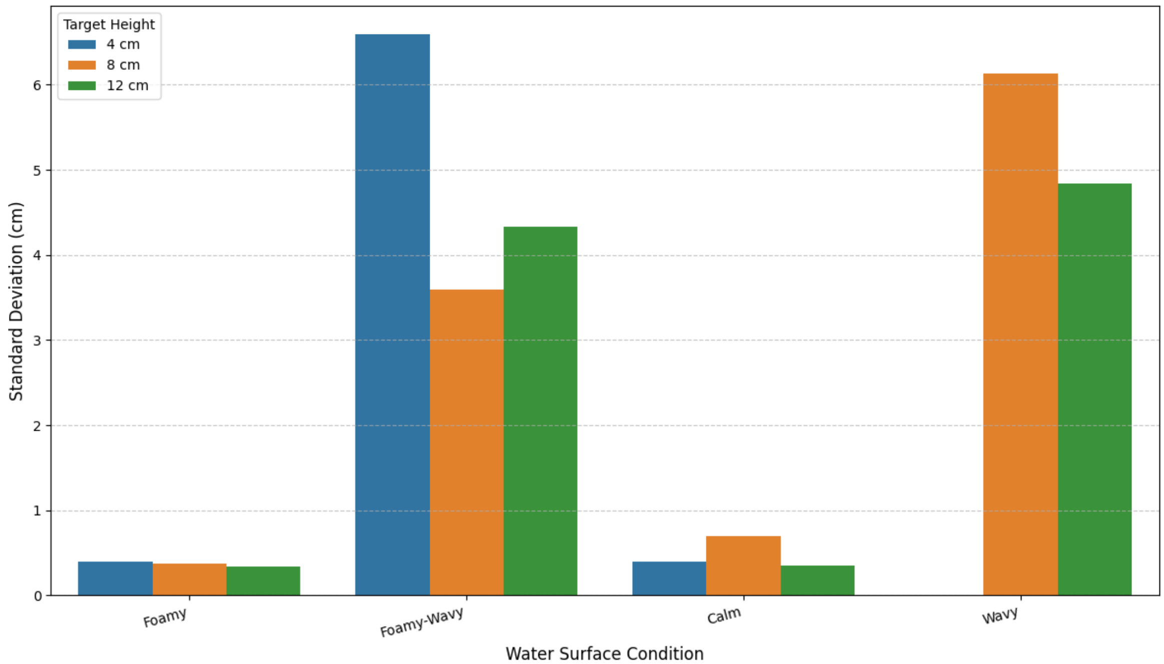

Figure 3. Standard Deviation Comparison Across Water Conditions

Control System Performance

The closed-loop control system was tested for its responsiveness and reliability.

1. Fill Cycle: When the water was manually drained below the MIN_LEVEL (7 cm), the system correctly detected the low level and activated the inflow (top) tap. The water level rose steadily. When the sensor's reading (potentially with a moving average filter) exceeded the MIN_LEVEL, the tap remained open until it reached the MAX_LEVEL (11 cm), at which point the tap successfully closed.
2. Drain Cycle: When water was added to exceed the MAX_LEVEL (11 cm), the system activated the outflow (bottom) tap. The water level lowered, and the tap closed once the level fell below the MAX_LEVEL. The system performed reliably in all four water conditions, though the "chatter" (rapid on/off switching) of the relay was slightly higher in wavy conditions, a problem that could be solved with software-based hysteresis (Purnama & Silaen, 2021).

Monitoring Applications

The web and mobile monitoring applications were successfully developed to interface with the backend system. Figure 4 shows the dashboard of the mobile application, developed using Flutter. The interface provides a clear, real-time visualization of the current "Ketinggian Air" (Water Level) as reported by the sensor. It also displays the live status of the "Kran Atas" (Top Tap) and "Kran Bawah" (Bottom Tap), indicating whether they are 'On' or 'Off'. Furthermore, a historical chart, labeled "Data Ketinggian Air," logs past measurements, allowing the user to track water level trends over time. This dashboard validates the front-end component of the system, providing an effective interface for both real-time monitoring and manual override of the controls.

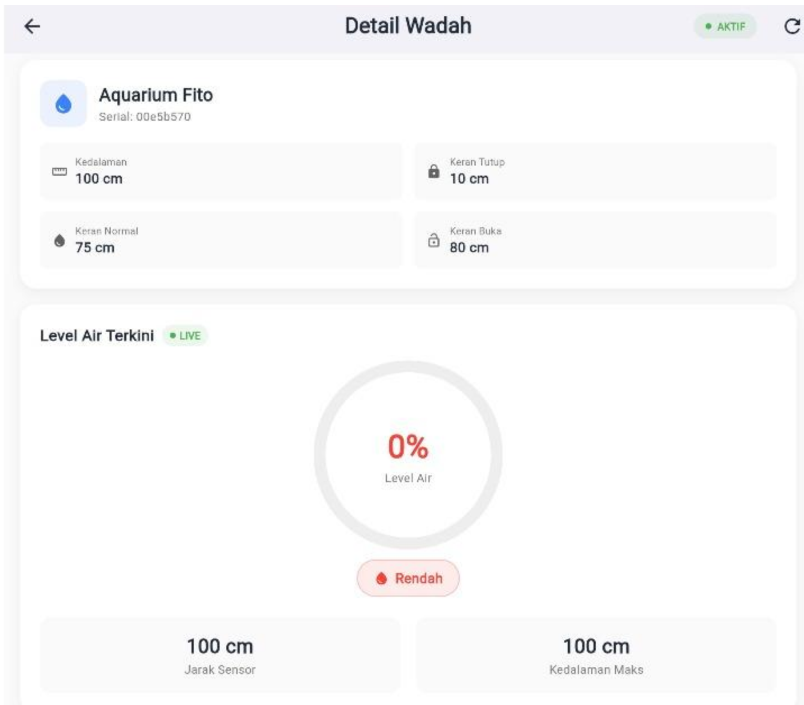

Figure 4. The Mobile Application (Flutter) Monitoring Dashboard

DISCUSSION

Interpretation of Findings

The results confirm that the HY-SRF05 ultrasonic sensor is a reliable and cost-effective choice for automated water level control, even in dynamic surface environments. The sensor's accuracy in calm conditions was high, consistent with manufacturer specifications. The most significant finding is its performance in wavy and foamy conditions. The increased standard deviation in wavy conditions is an expected physical phenomenon, not a sensor failure (Azmi & Rahmawati, 2021). It accurately reports the changing distance. For a control system, this "noise" can be effectively managed using simple data filtering techniques, such as a moving average or a Kalman filter, to smooth the readings before they are fed to the control logic (Dewi dkk., 2021). The sensor's ability to "see through" or at least get a consistent reading from the foam layer (with only a minor bias) is a noteworthy advantage. This suggests that for foam types similar to that in the experiment, the ultrasonic signal is not completely absorbed or scattered. The infrared sensor's failure underscores the critical importance of matching sensor specifications (specifically minimum detection range) to the application's physical constraints.

Relationship to Literature These findings align with broader consensus in the field regarding the utility of ultrasonic sensors (Azmi & Rahmawati, 2021). However, a critical distinction exists between this work and prior studies. While Azmi & Rahmawati (2021) primarily focused on sensor linearity under static water conditions, our study extends this validation into dynamic environments, proving the sensor's viability where surface stability cannot be guaranteed.

Furthermore, the comparison regarding foam interference offers a significant advancement. Noviana (2022) previously identified foam as a qualitative obstruction that could impede sensor accuracy; however, that study did not quantify the extent of the error. In contrast, our empirical data provides a concrete quantitative baseline, demonstrating that the error margin remains within acceptable limits for non-precision industrial applications. Additionally, while Wilyanto et al. (2023) established foundational IoT monitoring frameworks, their work was limited to observation. Our system advances this by successfully implementing a closed-loop control mechanism capable of reacting to these diverse conditions in real-time, bridging the gap between passive monitoring and active automated management.

Relationship to Literature

These findings align with other studies that have championed ultrasonic sensors for liquid level measurement (Azmi & Rahmawati, 2021). However, this study provides a specific contribution by directly comparing four distinct surface conditions, including the often-overlooked "foamy-wavy" combination. While Noviana, 2022 noted that foam *could* be a problem (Noviana, 2022), our empirical data provides a quantitative baseline for the expected performance of the HY-SRF05 in such a scenario. The success of the closed-loop control system demonstrates a practical application that builds upon foundational IoT monitoring research done by (Wilyanto et al., 2023).

Limitations of the Study

This study was conducted in a controlled laboratory setting, and several limitations must be acknowledged. First, the experiment did not account for real-world environmental factors like wind, rain, temperature fluctuations, or debris, which could affect sensor performance and system durability. Additionally, the foam used was generated from dish soap; industrial or biological foam in aquaculture may have different densities and acoustic properties which could yield different results. Furthermore, the tests were short-term, and long-term deployment is needed to assess sensor drift, reliability of the electronic components, and potential system fouling. Finally, the "wavy" condition was qualitative and was not quantified in terms of specific wave height or frequency.

Implications and Future Work

The findings imply that this low-cost system is practical for applications like automated garden irrigation, residential pool management, and hydroponics systems. For more critical industrial applications, the system could serve as a solid foundation, though it would require more robust filtering and industrial-grade components. Future work should focus on several key areas. First, advanced filtering could be implemented by comparing different software filters moving average, median filter, Kalman filter to determine the optimal method for stabilizing readings in wavy conditions. Second, the system should undergo field deployment to test its long-term durability and performance against real-world environmental variables in an application like an outdoor swimming pool or an aquaculture tank. Another promising direction is the development of a simple machine learning model that can classify the water's surface condition (calm, wavy, foamy) based on the sensor's signal variance, which could then automatically adjust the filtering algorithm. Finally, sensor fusion could be explored by integrating a secondary, cheaper sensor (like a simple float switch) as a fail-safe mechanism to enhance system reliability.

CONCLUSION

This research successfully designed, implemented, and validated a complete IoT-based system for automated water level control. The rigorous validation phase confirmed the HY-SRF05 ultrasonic sensor as a robust choice, demonstrating high accuracy with a Mean Absolute Error (MAE) consistently below 0.8 cm at operational levels (8 cm and 12 cm), even under challenging wavy and foamy conditions. In contrast, the infrared sensor proved unsuitable for short-range measurements. While the system performed reliably in most scenarios, limitations were observed in extremely shallow and turbulent conditions (4 cm). The integrated web and mobile applications successfully provided real-time monitoring and control interfaces. This study offers a practical, low-cost blueprint for automated water management. Future work will focus on implementing advanced filtering algorithms, such as Kalman filters, and conducting long-term field deployment to further enhance system resilience against environmental variables.

REFERENCES

Azmi, R., & Rahmawati, R. (2021). Perancangan aplikasi todolist berbasis Android menggunakan Flutter SDK dan database SQLite. Seminar Nasional Riset dan Inovasi Teknologi (SEMNAS RISTEK), 5(1).

Damayanti, S., Pelawi, B., & Manan, S. (2016). Sistem monitoring volume air menggunakan sensor ultrasonik dan monitoring output volume air menggunakan flow meter berbasis Arduino. Jurnal Fisika dan Aplikasinya, 19(2).

Daniesar, M. N., Dewi, T., & Oktarina, Y. (n.d.). Aplikasi sensor ultrasonik dalam pembacaan level air pada sistem pertanian aquaponic. Jurnal Teknik Elektro dan Komputer. https://doi.org/10.5281/zenodo.8031245

Dewi, I. Z. T., Ulinuha, M. F., Mustofa, W. A., Kurniawan, A., & Rakhmadi, F. A. (2021). Smart farming: Sistem tanaman hidroponik terintegrasi IoT MQTT panel berbasis Android. Jurnal Keteknikan Pertanian Tropis dan Biosistem, 9(1), 71–78.

Musawi, A. M. A., Al-Delphi, M. N., & Al-Zaidi, G. S. G. (2020). Water level monitoring and control system based on Internet of Things (IoT). Journal of Physics: Conference Series, 1530, Article 012061. https://doi.org/10.1088/1742-6596/1530/1/012061

Nurlaili, D., Ainun Qolbi, M., Halimatusa, N., & Maulidah, A. (2021). Perancangan flood warning alarm sederhana dengan indikator ketinggian berbasis tenaga panel surya. *DIFFRACTION: Journal for Physics Education and Applied Physics*, 3(2). http://jurnal.unsil.ac.id/index.php/Diffraction

Prasetya, E., Achmadi, S., & Rudhistiar, D. (2022). Penerapan IoT (Internet of Things) untuk sistem monitoring air dan controlling pada kolam ikan gurami berbasis website. Jurnal Mahasiswa Teknik Informatika, 6(2).

Purnama, F., & Silaen, S. (2021). Sistem informasi pemesanan online pada situasi kafe and resto. FORTECH (Journal of Information Technology), 5(1), 1–6.

Soambaton, M. F., Djuniadi, D., & Al-Azhari, A. H. (2024). Monitoring kolam ikan nila berbasis IoT dengan sensor amonia, suhu, ketinggian, dan pH. Jurnal Informatika dan Teknik Elektro Terapan, 12(2). https://doi.org/10.23960/jitet.v12i2.4021

Widayaka, P. D., Hadi, S., Labib, R. P. M. D., & Marzuki, K. (2022). Komparasi performansi sensor sebagai perangkat pengukuran ketinggian air pada sistem notifikasi banjir. Jurnal Bumigora Information Technology (BITe), 4(1), 37-48. https://doi.org/10.30812/bite.v4i1.1997